

Moodle and Affective Computing: Knowing Who's on the Other Side

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Abstract: In traditional learning, teachers can easily get an insight into how their students work and learn, and how they interact in the classroom. However, in online learning, it is more difficult for teachers to see how individual students behave and learn, and very important, their mood to do it. Student's emotions like self-esteem, motivation, commitment, and others that are believed to be determinant in student's performance can not be ignored, as they are known (affective states and also learning styles) to greatly influence student's learning. This paper deals with the student's behavioural and affective aspects in virtual learning environments to enhance the students' learning, gain and experience. The goal is to achieve a similar performance to a skilled teacher that can modify the learning path and his teaching style according to the feedback signals provided by the students - which include cognitive, emotional and motivational aspects. This can be done through the recognition of students actual mood, and we propose a framework to implement and address such issues in Moodle.

Keywords: Affective Computing, Learning Styles, E-learning, Moodle

1. Introduction

Since we've become teaching, providing knowledge to all that seek for it, with individualized support whenever it's needed (anytime, anywhere), when solicited, ideally even when that support isn't asked but the need for it is there, has been the ultimate goal search for everyone. In traditional learning, teachers can easily get an insight into how their students work and learn, and how they interact in the classroom. However, in online learning, especially when using systems like learning management systems (LMSs), and others, for instance Moodle, it is more difficult for teachers to see how individual students behave and learn, specially to characterize student's emotions like self-esteem, motivation, commitment, and others that are believed to be determinant in students performance. This paper deals with the student's behavioural and affective aspects in virtual learning environments, not always noticed and taking into account. Behavioral aspects are understood in terms of motivational factors such as confidence, effort, and independence for instance. They are important to infer the student's mood (interested/disinterested, satisfied/dissatisfied). As Moodle is one if not the most E-learning platforms used worldwide, also in portuguese schools, it will be used experimentally to try and develop a new affective module to address students' affective states and learning styles. The goal as stated, is to try to attend to students particularities, thus improving learning and success. We start in section 2 by clarifying the need for such abilities in Moodle. Later in section 3, affective computing, affective states and learning styles are briefly revised, in order to present in section 4 a framework for addressing some of the problems identified. The framework presented is part of an ongoing larger work that aims to develop a system to improve students' learning success, when using Moodle.

2. E-learning and Moodle

Currently, education organizations can not exclude them selves from information society, and are always confronted with new technological challenges. The student population comes from very different social backgrounds, with different needs and expectations. Moreover, society is demanding for more qualified technicians. Schools are, therefore, faced with a new technological paradigm, a new kind of public and new demands from society.

Education organizations have tried to address these challenges by investing in organization, management, market research, and in human and technological resources. New pedagogical tools, such as e-Learning platforms and Intelligent Tutoring Systems have been also subject of attention. These investments are very expensive; schools cannot afford to have unsuccessful students. As a consequence, the students' careers must be closely followed. Schools should have devices to evaluate their students' learning state, i.e., they should possess means to keep their students' descriptions up to

date, that way being able to follow and diagnose, if not in real time, at least periodically, the learning paths, to avoid failures as much as possible. Furthermore, the need to supply the market with effectively qualified personnel favours these evaluations (Almeida et al, 2008).

This evaluation and following should be performed by teachers and psychologists, who access and diagnose the learning paths of the students to detect symptoms of deviations and act accordingly. However, this kind of expertise isn't always available, and when it is, it's insufficient to address all the needs.

The need for some e-learning system that provides these features is then obvious. E-Learning systems are software programs that help and provide support to learning. They include personal training systems, usually designed for a certain knowledge domain, known as Tutoring Systems (VanLehn, 2006), as well as general learning management tools suitable to manage distinct types of learning content, covering several knowledge domains. Pedagogical concerns when building such systems aren't always present, but some attempts have been made. In (Rodrigues et al, 2005) a framework is proposed to mitigate some of these known problems.

Learning Management Systems/Course Management Systems (LMS/CMS) are domain independent, general purpose programmes/platforms, which provide authoring, sequencing, and aggregation tools that structure content to ease the learning process. MOODLE platform is an example of a LMS/CMS. It is widely used and the number of installations is growing very rapidly. In fact Moodle is by far, the most used e-learning platform in secondary schools in Portugal. Its usage has been widely recommended and encouraged by the official education organizations (Valente, 2007).

2.1. The MOODLE Learning Management System

MOODLE (Modular Object-Oriented Dynamic Learning Environment) has a number of interactive learning activity components like forums, chats, quizzes and assignments. In addition, MOODLE includes a logging module to track users' accesses and the activities and resources that have been accessed. Administrators and teachers can extract reports from this data. Figure 1 shows a high level view of the MOODLE modules.

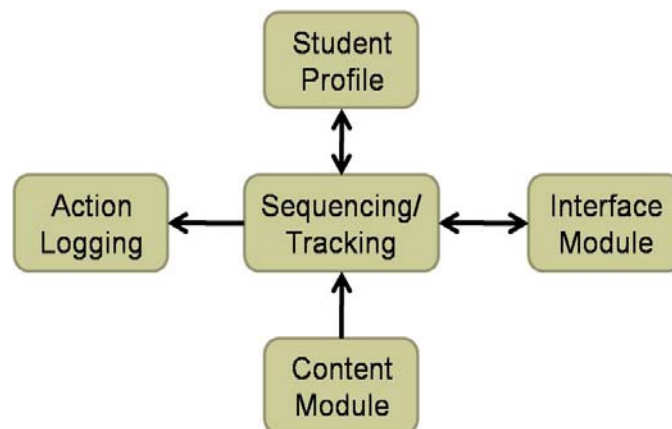


Figure 1- MOODLE LMS modules

By having a modular type design, the platform can be enriched with different plug-ins, designed to meet specific needs a specific set of users.

Whatever the case, LMS (Learning Management Systems) should have some sort of knowledge about the students and about their learning processes. This knowledge, i.e., the beliefs the system has about the students, is usually called the Student Model (SM). Without a SM a system would simply behave the same way for all students. Additionally, this Student Model must be dynamically upgraded to reflect students affective states, motivation, etc, to adapt not only to different students, but also to the different states that a student has, when using such a platform.

LMS, such as Moodle, are very successful in e-education but they do not accommodate full fledged adaptively (Graaf, 2006).

Moodle doesn't provide any of the issues previously discussed, and the need for some module that implements them it's crucial to improve student's success. In section 3, some of the important aspects

to consider, regarding students, their emotions and learning styles, in an e-learning platform are subject to a brief analysis. Later we will present a framework to implement and address such issues in Moodle.

3. Affective computing

Affective computing has emerged as a study area of Artificial Intelligence, whose objective is the study of emotions and their application in computer systems. According to (Picard, 2000), studies how computing systems can detect classify and respond to human emotions. Affective computing in Human-Computer Interaction can be defined as "computing that relates to, arises from, or deliberately influences emotion" (Picard, 2000). Various studies support that affect plays a critical role in learning performance as it influences cognitive processes (LeDoux, 1998).

"The extent to which emotional upsets can interfere with mental life is no news to teachers, students who are angry, anxious, or depressed have difficulties in learning; people who are caught in these states do not take information efficiently or deal with it very well", (Goleman, 1995). However, the relationship between learning and emotions is far from being that simple and linear.

Positive and negative affect states produce different kind of thinking and this might hold important implications from educational and training perspective. A consistent theory of learning that integrates effectively cognitive and emotional factors is strongly needed, (Kort, 2001).

A wide range of emotions occurs naturally in a real learning processes, from positive ones (joy, satisfaction, etc.), to negative ones (frustration, sadness, confusion), to emotions more related to interest, curiosity and surprise in front of a new topic. Emotion is characterized by "any agitation or disturbance of mind, feeling, passion; any vehement or excited mental state. There are a hundred emotions along with their combinations, variations and mutations. In fact, there are more subtleties of emotions than the words we have to define them." Already affection means briefly "the whole realm of emotions properly said, the feelings of emotions, sensory experiences, and especially the ability to be able to get in touch with the sensations" (Bercht, 2001).

Emotions have a close relationship to education, because the affective state of the student directly affects the motivation and aptitude to learn something. Thus, knowing the user's affective state might play an important role improving the effectiveness and efficacy of e-learning. The unawareness of emotional states has been considered one of the core limitations of the traditional e-learning tools. Skilled teachers modify the learning path and their teaching style according to students feedback signals (which include cognitive, emotional and motivational aspects), e-learning platforms generally don't take into account these feedbacks signals resulting too rigid and weakened, as they perform the same manner for all students.

A number of projects are currently being conducted in order to design e-learning platforms endowed with affective computing capabilities, although very few or no commercial results are currently available. (Balestra, 2005).

3.1. Affective States in E-learning

Most of the e-Learning systems focus attention towards knowledge acquisition or cognitive processing. When building such a system, affective states (such as motivation and emotion for instance), are considered only in terms of how the content is structured and presented. To make learning efficient and to deliver personalized content, adaptive systems are based on student's goals models, knowledge, and preferences. Thus, a student model that integrates the cognitive processes and motivational states would lead to more efficient and personalized adaptation, (Cocea 2007). Transforming a non-affect sensitive e-learning system into a system that includes user's affective states requires the modelling of a cycle known as the affective loop. The affective loop encompasses detection of a user's affective states, appropriate actions selection for decision making, and the synthesis of appropriate affective state by the system, (D'Mello, 2008).

As stated before, affection influences the learning performance and decision making. This means that students who become caught in affective states such as anger or depression do not process and absorb information efficiently. From this, it can be inferred that a user's affective state has a major role in improving the effectiveness of e-learning, (Weimin 2007).

"Emotion, mood and affective attitude are different things but strongly related and influence each other. An emotion is "composed" by a facial expression, a feeling (the conscious experience of the emotion) cognitive processing aimed at evaluating the situation in terms of personal relevance, physiological change and action readiness. It's a short but intense episode, (for instance I feel and noticed I am happy when seeing an old friend). In contrast, mood refers to the presence of moderate levels of affect. Mood is not consciously attributed to a causal factor. I can feel frustrated for half a day not knowing why. An affective attitude is an affective association coupled with a thing or person, an emotion is an evaluation of a thing or person in terms of personal relevance", (Broekens, 2010).

In this work, we will use the term mood in order to determinate or name a student's particular state of mind or emotion, that is, a particular inclination or disposition to learn something.

Numerous parameters can be used to describe students' affective states, motivation and interest, for instance. Confidence, effort and confusion are highlighted among the possible factors influencing a student's motivation (Qu, Wang, and Johnson 2005).

Also, the motivational model presented by (De Vicente and Pain, 2002) includes variables related to trait (control, challenge, fantasy, and independence) and state (confidence, sensory interest, cognitive interest, effort, and satisfaction).

In (Khan, 2010a), 4 methods to infer student's affective states are proposed, namely verbal approach, where a questionnaire or self report instrument is presented to the student, nonverbal approach where psycho-physiological instrument measures physical states, through the use of sensors, intrusive approach through the use of intrusive instruments to measure affective states, (although that intrusive instruments influence a student's normal affective state and may thus lead to misinformation), and non-intrusive approach where the affective state is identified through interaction with the system.

Another model, known as OCC, is frequently referred also as the standard cognitive appraisal model that provides a clear and convincing structure of the eliciting conditions of emotions and the variables that affect their intensities. This psychological model is popular among computer scientists that are building systems that reason about or incorporate emotions, (Ortony, Clore, & Collins, 1990).

3.2. Learning Styles

The idea that students learn differently is valued and probably had its origin with the ancient Greeks. For many years, it has been noticed that some students prefer certain methods of learning more than others. These dispositions, form a student's unique learning preference that is, student learning style, and aid educators in planning small-group and individualized instruction. (Grasha 1996), has defined learning styles as, "personal qualities that influence a student's ability to acquire information, to interact with peers and the teacher, and otherwise participate in learning experiences". There are probably as many ways to "teach" as there are to learn.

Learning styles specify a student's own way of learning. Someone that has a specific learning style can have difficulties when submitted to another learning style (Felder, 1988). When the presenting instruction style matches the student's learning style, the process is maximized, that is, the student learns more and better. Based on literature, we can establish that the consideration of learning styles in a learning environment influences a student's learning. In the present era, learning styles are being investigated in order to incorporate them into adaptive online learning environments (Graf, 2006).

Adaptive online learning environments are ideal for generating learning style based instructional material in large classes as they do not have the same limitations as human instructors that due to the lack of resources and time are unable to focus on individual students. One popular learning style inventory and one that is often used in distance learning research is the Kolb Learning Style Inventory (LSI). Kolb's LSI measures student learning style preference in two bipolar dimensions, (Kolb, 1986).

Other several learning style theories exist, for instance, Honey and Mumford (Honey, 1982) and Felder-Silverman learning style model (Felder, 1988). The later seems to be the most appropriate for use in e-learning systems (Carver et al., 1999). Most other learning style models classify learners in few groups, whereas FLSM describes the learning style of a learner in more detail, distinguishing between

preferences on four dimensions. In (Graaf, 2006) a very interesting work is proposed to automatically detect learning styles through student modelling.

Table 1 – Learning styles adapted from (Shahida, 2008)

Learning Style	Characteristics
Active	Tries things out, works within a group, discusses and explains to others
Reflective	Thinks before doing something, works alone
Sensing	<i>Learns from and memorizes facts, solves problems by well-established methods, patient with details, works slower</i>
Intuitive	Discovers possibilities and relationships, innovative, easily grasp new concepts, abstractions and mathematical formulation, works faster
Visual	Learns from pictures, diagrams, flow charts, time lines, films, multimedia content and demonstrations
Verbal	Learns form written and spoken explanations
Sequential	Learns and thinks in linear/sequential steps
Global	Learns in large leaps, absorbing material almost randomly

Currently two approaches are used for identifying learning styles, namely the use of questionnaires and the use of data from students' behaviour and actions in an online course. Shute and Zapata-Rivera (Shute, 2008), identify at least two problems associated with questionnaire based information. Students may provide inaccurate data either purposefully, (for instance a desire to present themselves in a more prominent way) or accidentally, due to not knowing their own characteristics. A second problem is that when completing the questionnaire during the online learning process, it consumes time, and students tend to provide invalid data in order to shortcut to contents quickly. As stated, Felder and Silverman developed an Index of Learning Styles Questionnaire (ILS) that is widely used to identify learning styles explicitly (table 1).

An approach based on the actions and behaviour of the students during their interaction with the system for learning may be used. No additional effort is needed by students in these approaches in order to obtain information about their learning styles. In fact learning styles are inferred by the system from the student's actions, being the information captured that way free from uncertainty. In (Khan, 2010a) a concept for identifying learning styles and affective states, using different approaches is proposed.

In the next section, a Framework is presented, to mitigate some of the problems elicited before, regarding e-learning platforms', namely Moodle.

4. The Framework

In figure 2 we present a framework to address some of the problems identified through this work. The goal is to obtain an external module, to be linked to Moodle platform, enabling the detection of student's affective states together with learning styles, in order to really know each student and presenting contents accordingly. The affective module will be responsible for gathering all this information, and derive students mood (referred in this work as students particular state of mind or emotion, that is, a particular inclination or disposition to learn something), in order to present relevant clues for a personalization and recommendation module (not detailed in this paper).

The affective module has two sub-modules, explicit assumption and implicit assumption, whose function is to detect student's mood, maintaining that information (actual and past) in the mood database, that will be used by another sub module, affective adaptative agent to provide relevant information to the platform and to the referred personalization module. This enables that actual students mood information can be displayed in Moodle platform, and may be used to personalize instruction according to the specific student, thus enabling Moodle to act differently to different students, and also to act different to the same student, according to his/her past and present mood.

The sub-modules are explained next. We are not developing integrally all the modules from scratch, various research has been done in areas as facial recognition, keyboard and mouse stress detection, for instance, that can be used here. Many research in log analyses for student characterization is also widely available.

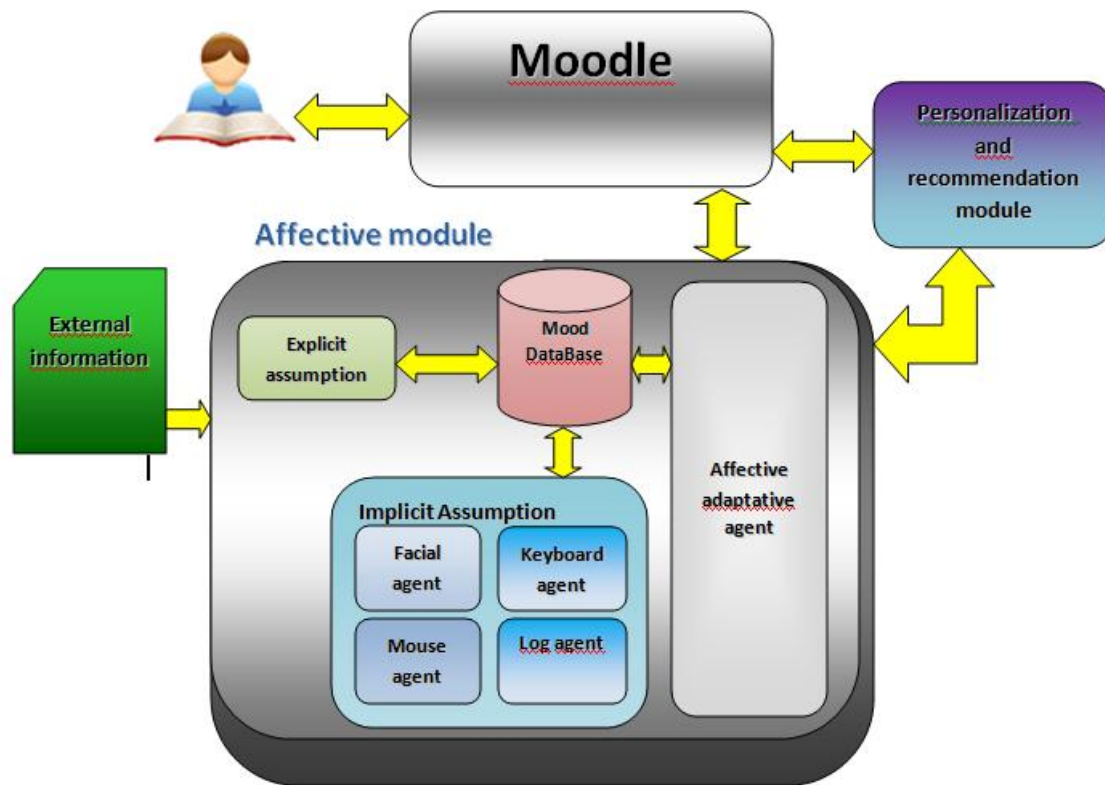


Figure 2 – The proposed Framework

4.1. Explicit mood assumption

One (the easiest way but not the most accurate) form of knowing a student's mood to achieve a certain class is by posing explicit questions to the student. Surprisingly, this may not be the most accurate way, not always the answers obtained reveal the accurate state of the student. However we can still use questionnaires, as a way of gathering some useful information. An explicit mood assumption agent could periodically pose some questions, preferably in a visual way, for the student to upgrade his/her mood to the system. Several researches have been done to detect student mood explicitly (Broekens et al,2010).

4.2. Implicit mood assumption

The aim of this sub-module is to monitor the interactions between the student and the system, in order to infer the students' mood, doing so without being intrusive, that is, without the student being aware of the analysis being performed. Agent technology is used to monitor four key aspects: facial analyses, mouse analyses, keyboard analyses and log analyses. As web cams tend to be widely standard equipment in computers, the goal is to use it to try to infer emotions from the user. Mouse movements can also predict the state of mind of the user, as well as keyboard entries. Finally, analysing the past interactions of the student, through the logs files of Moodle, turns possible to infer some of the information we are looking for.

Facial recognition

As stated, and as it is widely recognized from psychological theory, human emotions can be classified into six archetypal emotions: surprise, fear, disgust, anger, happiness, and sadness. Facial motion

plays a major role in expressing these emotions. Several automatic emotion recognition systems have explored the use of facial expressions to detect human affective states. (Cohen et al,2003),(Pantic, Rothkrantz, 2000).

The main idea is to extract affectively relevant features from an image, in order to establish the student current emotions, features like mouth angle and face movements are used. Doing this implicitly makes more difficult to deceive the system, as the student isn't aware of the on going analyses.

Keyboard and Mouse

The way a user types, may indicate his/her state of mind. Pressing hard and rapidly the keyboard could mean an altered state, anger for instance, while taking too much time may mean sadness for instance. The same occurs with mouse movements. A system that monitors users' behaviour from standard input devices, like the keyboard or the mouse is proposed by (Zimmerman et al. 2003). Analyzed features include: the number of mouse clicks per minute, the average duration of mouse clicks (from the button-down to the button-up event), the maximum, minimum and average mouse speeds, the keystroke rate (strokes per second), the average duration of a keystroke (from the key-down to the key-up event) and performance measurements. (George, Tsihrintzis et al., 2008) included keyboard –stroke information in order to improve the accuracy of visual-facial emotion recognition.

Log agent

Moodle has an activity logger to register users' accesses (i.e., user ID, IP and time of access) and the activities and resources that have been accessed. From the log, Moodle is able to generate, for each student, activity reports. In (Khan 2010b), learning styles and affective states information are gathered from students' interactions in a web-based learning management system. The students' behaviour on features that are commonly used in Moodle is analysed. Those commonly used features include content objects, outlines, exercises, self assessment tests, examples, discussion forums for assignment related queries, discussion/peer rating forums related to the content objects, and assignments. Considering information from all these features, the students' learning styles as well as affective states can be identified using a rule- based approach.

In our work, we are using non-invasive techniques because we believe that's the best way to do it. We believe that more intrusive techniques, like body sensors, heart monitors, etc are not well accepted by users. Another interesting point to refer is that using this kind of technologies (web cam, mouse and keyboard analysis) makes our solution cheaper, versatile and virtually undetected by users, making the inference from interactions more reliable.

5. Conclusions

Through out this paper, some major problems regarding E-learning platforms, namely Moodle where identified. The importance of students' individual characteristics, as the way they learn and the mood in which they do it, outstands as a crucial learning factor. Nevertheless, as stated, E-learning platforms don't take into account these issues. The Framework proposed tries to solve them, by the inclusion of an affective module in Moodle. The affective module proposed, tries to identify learning styles and students affective states that are widely recognized to be of great importance for learning success. The use of implicit methods to do this is emphasised, as the student doesn't need to be aware of the ongoing analyses, thus the probability of deactivating the system gets lower. Several research has been done in these methods, facial emotion recognition, mouse and keyboard emotion detection and also log analyses. Detecting affective states and learning styles will enable our recommendation module to do more effective recommendation namely in terms of content presentation. We hope to use the results of such research, in order to develop the affective module. We're not trying to develop from scratch such methods. Experimentation and testing will be done through the implementation of a real system in public secondary school in Portugal. This is part of a larger project as stated.

References

- Almeida P., Novais P., Costa E., Rodrigues M., Neves J. (2008): Artificial Intelligence Tools for Student Learning Assessment in Professional Schools, in Proceedings of the 7th European Conference on e-Learning, Cyprus, ISBN 978-1-906638-22-1, pp 17- 28,.
- Balestra, M. (2005): I progetti di ricerca CRAFT nel VI Programma Quadro: MySelf. E-Learning & Knowledge Management.
- Bercht, M. (2001) "Em direção a agentes pedagógicos com dimensões afetivas". Tese de Doutorado (Doutorado em Ciência da Computação)-Universidade Federal do Rio Grande do Sul, Porto Alegre.
- Broekens, J, Jonker, C.M., Meyer, J.J.Ch, (2010): Affective negotiation support systems, Journal of ambient Intelligence and smart Environments, vol2, n. 2
- Carver, C.A., Howard, R.A. and Lane, W.D., (1999): Addressing different learning styles through course hypermedia. IEEE Transactions on Education, Vol. 42, No. 1, pp. 33-38.
- Cocea, M., Weibelzahl, S. (2007). Eliciting motivation knowledge from log files towards motivation diagnosis for Adaptive Systems. User Modeling 2007 LNCS Springer Berlin / Heidelberg.
- Cohen, I. ,et al. (2003):Facial expression recognition from video sequences: Temporal and static modeling. Computer Vision and Image Understanding, 91(1- 2):160–187.
- D'Mello, S. K., Craig, S.D., Witherspoon, A., McDaniel, B., and Graesser, A., (2008). Automatic Detection of Learner's Affect from Conversational Cues. Journal of User Modeling and User-Adapted Interaction, 18(1-2), 45-80.
- De Vicente, A. Pain, H. (2002): Informing the Detection of the Students' Motivational State: An Empirical Study, Proceedings of the Sixth International Conference on Intelligent Tutoring Systems, vol 2363 of Lecture Notes in Computer Science, pages 933-943
- Felder, R.M. and Silverman, L.K., (1988): Learning and teaching styles in engineering education. Engineering Education, Vol. 78, No. 7, pp. 674–681.
- Gilbert, J.E., Han, C.Y. (1999): Adapting Instruction in Search of a Significant Difference, Journal of Network and Computer Applications, 22(3), pp 149-160
- Graf, S., Kinshuk. (2006): An Approach for Detecting Learning Styles in Learning Management Systems, in Sixth IEEE International Conference on Advanced Learning Technologies. Kerkrade, Netherlands, pp. 161-163
- Grasha, A. F. (1996). Teaching with style. Pittsburgh, PA: Alliance.
- Graf, S. (2007): Adaptivity in Learning Management Systems Focusing on Learning Styles, Ph.D Thesis, Vienna University of Technology
- George A. Tsihrintzis, Maria Virvou, Efthymios Alepis, Ioanna-Ourania Stathopoulou, (2008). Towards Improving Visual-Facial Emotion Recognition through Use of Complementary Keyboard-Stroke Pattern Information. itng, pp.32-37, Fifth International Conference on Information Technology: New Generation.
- Goleman, D. (1995): Emotional intelligence. Bantam Books, New York
- Honey, P. and Mumford, A., (1982). The manual of learning styles, Peter Honey, Maidenhead.
- Jonassen, D. H., Grabowski, B. L. (1993): Handbook of Individual Differences, Learning and Instruction. Lawrence Hillsdale, NJ: Erlbaum Associates
- Khan,F.A., et al (2010a): Identifying and Incorporating Affective States and Learning Styles in Web-based Learning Management Systems, Interaction Design and Architecture(s) Journal - IxD&A, N. 9-10, pp. 85-103

Khan,F.A., et al (2010b): Implementation of Affective States and Learning Styles Tactics in Web-based Learning Management Systems, 2010 10th IEEE International Conference on Advanced Learning Technologies

Kort, B., Reilly, R. (2001): Analytical Models of Emotions, Learning and Relationships: Towards an Affect-sensitive Cognitive Machine. MIT Media Lab Tech Report No 548

Kolb, D. A. (1986). Learning style inventory: Technical manual (Rev. ed.). Boston, MA: McBer.

LeDoux, J. (1998): The emotional brain: The mysterious underpinnings of emotional life. Weidenfeld & Nicholson, London

Ortony, A., Clore, G.L., Collins, A. (1988): The Cognitive Structure of Emotions. Cambridge University Press, Cambridge, UK

Pantic, M. Rothkrantz, L.J.M. (2000): Automatic analysis of facial expressions: the state of the art. IEEE Trans. PAMI, 22(12): 1424–1445,

Picard, R. (2000) "Affective Computing". The MIT Press, ISBN: 0262661152.

Picard, R. W., Papert, S., Bender, W., Blumberg, B., Breazeal, C., Cavallo, D., Machover, T., Resnick, M., Roy, D., Strohecker, C. (2004): Affective Learning - A Manifesto. BT Technology Journal Vol. 22, 4 253-269

Qu, L., Wang, N., Johnson, W.Lewis. (2005): Using Learner Focus of Attention to Detect Learner Motivation Factors, In Ardissono, L., Brna, P., Mitrovic, A.: User Modelling 2005, pp 70-73

Rodrigues, M., Novais, P., Santos, M.F. (2005), Future Challenges in Intelligent Tutoring Systems – a Framework, "Recent research developments in learning technologies : proceedings of the International Conference on Multimedia and Information & Communication Technologies in Education, 3, [Cáceres], 2005" Badajoz : Formatex

Shahida M. Parvez and Glenn D. Blank, (2008): Individualizing Tutoring with Learning Style Based Feedback, [Intelligent Tutoring Systems, 9 th International Conference, Montreal, Springer.

Shute, V. J., Zapata-Rivera, D. (2008): Adaptive technologies, In J. M. Spector, D. Merrill, J. van Merriënboer, & M. Driscoll (Eds.), Handbook of Research on Educational Communications and Technology (3rd Edition) (pp. 277-294). New York, NY: Lawrence Erlbaum Associates, Taylor & Francis Group

VanLehn K. (2006) "The behaviour of tutoring systems", International Journal of Artificial Intelligence in Education, Vol. 16, No. 3, pp. 227-265.

Valente, L. & Moreira, P. (2007). Moodle: moda, mania ou inovação na formação? –Testemunhos do Centro de Competência da Universidade do Minho. In P. DIAS; C. V. FREITAS; B. SILVA; A. OSÓRIO & A. RAMOS (orgs.), Conferência Internacional de Tecnologias de Informação e Comunicação na Educação – Challenges 2007. Braga: pp. 781-790.

Weimin, X., Wenhong, X.(2007). E-Learning Assistant System Based on Virtual Human Interaction Technology, ICCS 2007, LNCS, Springer Berlin / Heidelberg.

Zimmermann, P., Guttormsen, S., Danuser, B., Gomez, P.(2003): Affective computing-a rationale for measuring mood with mouse and keyboard. International journal of occupational safety and ergonomics: JOSE vol. 9, issue 4, p. 539-551.